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Citation for published version:
Dunbar, A, Wallace, A & Harrison, G 2016, 'Energy storage and wind power: Sensitivity of revenue to future market uncertainties', *IET Renewable Power Generation*, vol. 10, no. 10, pp. 1535 – 1542.
https://doi.org/10.1049/iet-rpg.2016.0024

Digital Object Identifier (DOI):
10.1049/iet-rpg.2016.0024

Link:
Link to publication record in Edinburgh Research Explorer

Document Version:
Peer reviewed version

Published In:
IET Renewable Power Generation

Energy storage and wind power: Sensitivity of revenue to future market uncertainties

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Abstract: Grid connected electrical energy storage is expected to enable the integration of variable renewable generation in the future. As the electricity sector develops wholesale electricity prices will change, which will change the way in which storage technologies are operated. This paper investigates the sensitivity of storage revenue to uncertain market variables. Results indicate that higher gas prices, carbon prices and average demand would increase peak electricity prices, leading to larger daily price spreads and increased storage revenue. Increased wind generation, however, would reduce opportunities for price arbitrage and lessen storage revenue. Wind power also affects the way in which devices are operated and changes the characteristics which are rewarded by the market. With increased wind capacity, storage devices cycle less regularly as operation is driven by substantial changes in wind power output, rather than daily demand patterns. As a result, slower discharge times are more favourable and revenue is more sensitive to rates of self-discharge. Furthermore, there is less variation in wholesale electricity price and consequently conversion efficiency is more critical to performance.

1. Introduction

Electrical energy storage (EES) is regarded as a potential solution to the challenge of the Energy Trilemma in facilitating the grid integration of renewable energy. Many benefits of storage have been identified including improved system control, reduced network congestion and avoided curtailment of renewable output [1]. In the coming decades deployment of renewable energy capacity is expected to increase significantly leading to a greater requirement for flexibility and a higher value to be placed on these benefits.

There are expected to be bespoke applications, such as in islanded or heavily constrained networks, where business cases for storage would exist [2]. Storing renewable electricity until it could be consumed locally would be a more attractive option than upgrading transmission or distribution network connections in these cases. However, many renewable energy projects will not have the benefit of local consumers. These projects, particularly those located offshore, will be network-connected and will generate into a centralised energy system.

Grid connected electrical energy storage will be required to aggregate revenue streams from a range of markets if it is to be commercially viable [3] [4]. One recognised revenue stream is price arbitrage – purchasing electricity when it is cheap and selling it back to electricity suppliers during periods of peak demand when the price is high.

Several studies have investigated the revenue available to a storage operator through price arbitrage with [5], [6], [7], [8] and [9] using historic electricity prices to estimate revenue available under existing market conditions. [5] compared the performance of pumped hydro, hydrogen and battery storage devices in the Great Britain (GB) market from 2005-2010. The results demonstrated increasing revenue with charging rate and technology performance improving with efficiency. Other studies have investigated a single technology in multiple markets. [10] compared arbitrage value of pumped hydro plant in 13 different regions highlighting the dependence of revenue on local market conditions. [11] concluded that arbitrage value was dependent on the specific generation mix and fuel costs. As larger numbers of wind farms are deployed, the generation mix will change substantially and wholesale electricity prices will increasingly will be driven by wind power output in addition to demand cycles. Gas and carbon prices will also change in the future affecting the daily price spread. These may change the way in which storage devices are operated. Few authors have modelled arbitrage revenue in future electricity markets, however, [12] proposed a method to investigate this. Four storage technologies were examined in markets with increasing renewable energy capacity and the sensitivity of net present value was tested against a range of variables. The trading margin, or daily price spread, was highlighted as one of the most sensitive parameters. The model was not, however, capable of reflecting variations in gas and carbon prices in the price spread and consequently the effect of these on storage revenue. Furthermore, wind power was attributed a marginal value equivalent to the opportunity cost of a Renewable Obligation Certificate, which had the effect of driving costs negative. [13] investigated the impact of negative electricity prices on arbitrage revenue for storage and concluded that whilst creating some opportunities to gain additional revenue during periods of charging, their occurrence would be infrequent and would probably not impact technology choices for storage.

[14] used a similar approach to [12] implementing an alternative wind model, price function and including sufficient detail to reflect the impact of changing gas and carbon prices on arbitrage revenue. A single set of storage characteristics was investigated to show the changing annual revenue from 2020 to 2025 in the National Grid 2014 'Gone Green' Future Energy Scenario (FES). This scenario exhibited increasing wind capacity and higher gas and carbon prices, among other changes. The results suggested that increased wind power may lead to reduced arbitrage revenue, while increasing gas and carbon prices may increase revenue. However, these factors were investigated with a single scenario and the impact of their individual effects was not explicitly identified. Furthermore the impact of these changes on the storage operation strategy was not investigated, nor the implications of this on the device characteristics which would be most favourable in these conditions.

Using the model described in [14], this paper investigates the sensitivity of arbitrage revenue to changes in gas price, carbon price, capacity margin and wind power capacity in the GB market and the impact of these variables on the preferred device characteristics. The potential future value of these variables is highly uncertain and investors will need to understand how a storage investment will perform across a range of outcomes. Scenarios are a useful method for appraising uncertainty, but sensitivity studies allow the influence of individual factors to be investigated. It is critical that the relative importance of key storage characteristics is understood in the context of uncertain market variables. This will enable technology choices to be developed which are robust to changing market conditions instead of solutions which are optimal for today's market, but which may become redundant as the sector evolves. Table 1 compares the approach used in this study with other work investigating arbitrage revenue to highlight its contribution.

Table 1 *Comparison of scientific literature*

Paper	Market	Electricity Prices	Negative Prices	Sensitivities Investigated	Implications
Figueiredo et al [8]	Various	Historic	No	Alternative historic markets	Revenue varies significantly between markets, dependent on specific generation mix, market design and participant behaviour
Connolly et al [10]	Various	Historic	No	Market, year, optimisation strategy	Highlights variation in revenue between historic years, markets and optimisation strategies
Sioshansi et al [11]	PJM	Historic	No	Storage characteristics, forecasting, year	Highlights influence of gas price on arbitrage revenue from historic prices. Justifies use of perfect foresight
Grunewald et al [12]	GB	Future scenarios – varies wind / solar	Yes	Storage characteristics, generation mix	Concludes arbitrage may be commercially viable for low cost, long duration storage in future with large renewable capacity
Barbour et al [13]	GB	Historic (modified)	Yes	Storage efficiency and capacity	Negative pricing demonstrated to be beneficial to storage, but unlikely to have a major impact on technology choices
Imperial College [4]	GB	Future scenarios	No	Storage size relative to wind farm size	Focus on 'value of storage'; simple case study of wind farm.
This Paper	GB	Future scenarios – varies wind, gas and carbon prices	No	'Wind year', gas and carbon prices, wind capacity, storage characteristics	Sensitivity to wind power capacity, gas and carbon prices investigated (independently). Implications of wind-driven price profile on storage operation investigated.

2. Storage Revenue Model

The model comprises several components which estimate storage revenue in a simulated electricity system: an electricity market price model, a wind generation model and a storage arbitrage revenue model. Each of these components is explained fully in [14] which should be referred to for further details regarding the model assumptions and validation. A summary of the key features is given below.

2.1 Electricity market model

The electricity market price model was established on the assumption of perfect competition. This approach has been shown to be representative of the power exchange in GB and is commonly used for modelling scenarios of future electricity prices where variables are significantly different from historic levels [15]. The pricing model operates using estimated aggregate supply and demand functions where the price of electricity for each half hour time period is determined by the market clearing price. Thermal generators were grouped into four classes: nuclear, coal, combined cycle gas turbines (CCGT) and open cycle gas turbines (OCGT). The aggregate supply function was formed by stacking the generator classes in merit order of increasing marginal cost, C, which was calculated for each technology using:

$$C = \frac{1}{\eta}(aF + \nu F_{car}) + V + e \tag{1}$$

where η is thermal efficiency, F is fuel cost, ν is carbon emitted from combustion, F_{car} is the carbon price, V is variable generation cost, a is a conversion coefficient and e is the cost of nuclear fuel enrichment.

Competitive prices were assumed with marginal generators bidding a price between their own marginal generation cost and the cost of the next class of generator in the merit order stack (the fundamental costs and characteristics of each generator type are given in Table 2). Between these two values, a hyperbolic function was used to smooth the discontinuities in the step function and better represent the complexities of the supply curve, such as differing ages and efficiencies of plant within each generation type [14]. An exponential uplift in price which applies to OCGT to represent their ability to set high prices at extreme demand levels (and recover their fixed costs) [14]; similar approaches have been used by [16] and [17]. An example of the supply curve is shown in Fig. 1 where the merit order was nuclear, coal, CCGT then OCGT. The supply curve is notably flat in the regions where base load and mid merit generators fulfil demand. When peaking capacity is required, there is a sharp increase in price.

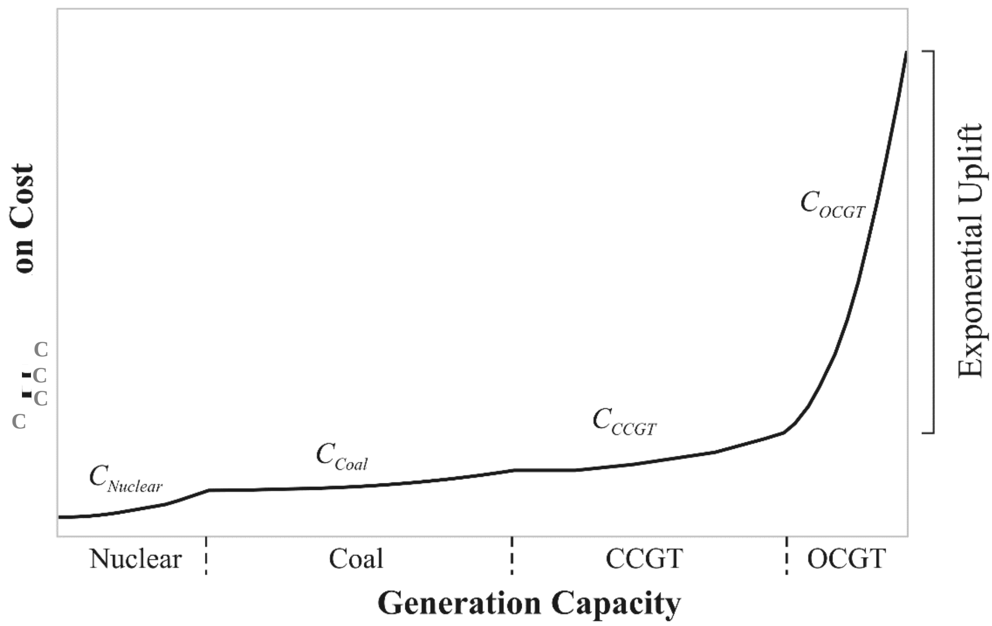


Fig. 1. *Example electricity supply curve.*

Table 2 Thermal generator data **[18] [19] [20]**

Generator Type	Thermal Efficiency η (%)	Carbon Emissions ν (kg/MWh)	Variable Operating Costs V (£/MWh)	Enrichment Cost e (£/MWh)	Availability (%)	Conversion Coefficient a
Nuclear	36	0	1.8	2.5	78	$8.24\text{x}10^{-3}$
Coal	36	285	2.0	0	86	150
CCGT	60	185	2.2	0	87	34.128
OCGT	46	185	2.7	0	95	34.128

Historic demand data from National Grid is used to drive the model and this defines the power which conventional generation must serve in each time period. It is common when modelling markets with wind generation to deduct aggregate wind output time series (Section 2.2) from the underlying electricity demand time series; it is this ‘net demand’ that the remaining generation is dispatched to meet and the resulting intersection with the supply curve defines the market price.

In practice only relatively small, embedded wind generation behaves as negative load with larger wind farms forecasting their output and trading in forward markets. As such, wind farm output would tend to adjust the supply function for each half-hour period. Thermal generation would be required to respond not only to changes in wind and demand, as well as forecast errors, indicating that the assumption that thermal plant is dispatched in merit order is a simplification. With significant market share of wind there is potential for market prices to not only be suppressed but in certain cases to become negative [21]. Firstly, wind may be the marginal generator and when in receipt of subsidy it may offer negative bids up to the subsidy level to avoid curtailment. Secondly, an inflexible baseload plant that otherwise would be shut down and re-started may seek to avoid the costs of doing so by offering negative bids to keep generating. The extent and occurrence of negative prices is, however, strongly dependent on a range of factors including the extent of wind generation, levels of demand and the specific subsidy regime in place [21]; they would be expected only at high levels of installed capacity and would tend to be relatively infrequent [21]. As the merit order model applied here does not account for the dynamics of generation dispatch, the assumption that no subsidies are paid for renewable generation means the minimum price of electricity never falls below zero. As such, the shape of the supply curve does not fundamentally change, remaining shallow at low net demand and steep during periods of high net demand.

Historic Market Index Prices from the UK power exchange [22] were used to calibrate and validate the market model. Data from 2005 to 2007 [14] was used as it represents a period prior to the major increase in wind generation in GB. Time series of historic fuel and carbon prices were sourced from [23], [24], [25] and [26]. Price data at as high a temporal resolution as possible was used; in the case of gas, daily prices were found to substantially better capture underlying electricity market price behaviour. This was deemed credible as although generators will purchase most of their fuel at fixed prices on forward markets, they may also trade on daily gas markets to adjust their position; this leads daily gas prices to better represent the marginal behaviour of gas generation.

The calibration was aimed at ensuring that the intraday spread in electricity prices – of critical importance to arbitrage revenue – was represented well by the model. The mean daily peak and trough prices are much more important for arbitrage than the extreme values and these were found to be captured well [14]. Across the 3 years, the absolute error (bias) for mean peak prices was £2.64/MWh and £5.64/MWh for mean trough values. When applied to the storage model (Section 2.3), the difference between the modelled and historic electricity prices resulted in revenue differing by at worst 10% in any one year and virtually zero on average. The quality of the fit is well demonstrated in Fig. 2 which shows the historic and simulated electricity prices for the first week in August 2007.

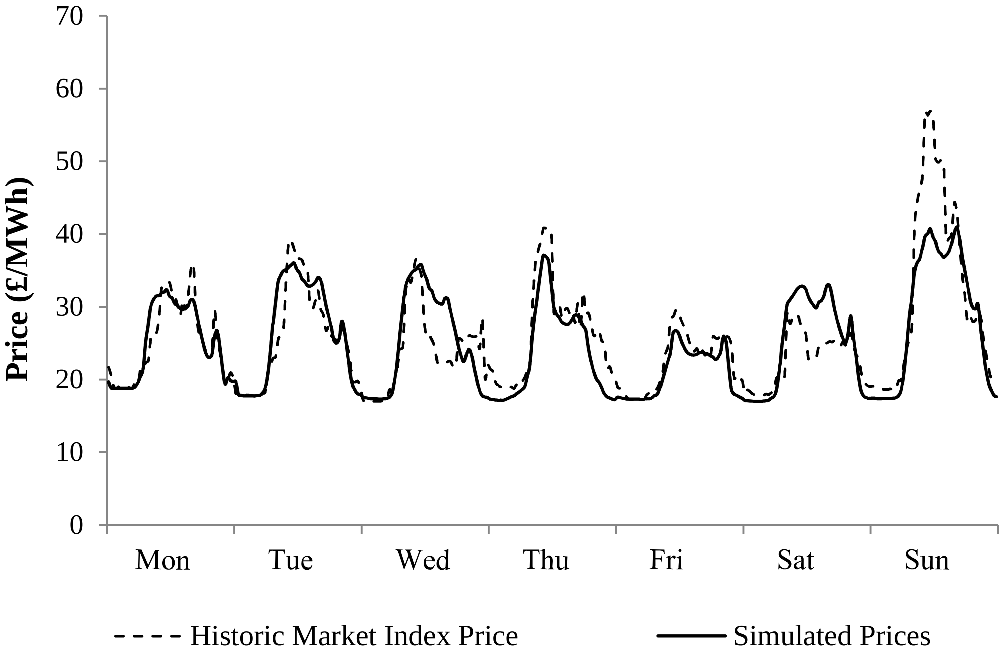


Fig. 2. *Historic market prices and simulated electricity prices for first week in August 2007*

2.2 Wind power production

Aggregate wind production time series were based on high resolution hourly wind simulations for the UK and surrounding waters produced by Hawkins [27]. The DECC RESTATS planning database [28] was used to identify the location and capacity of existing and planned wind farms in GB with the site-specific wind speed series extracted at each location. Power output from each wind farm was calculated using an equivalent aggregate power curve described in [27]. Depending on the assumptions about wind deployment this allows aggregate production for onshore and offshore wind fleets to reflect the diversity of wind speeds across the UK. Aggregate production was reduced by 10% to account for availability, a conservative assumption onshore but early offshore availability was less than 90% [29]. The data was interpolated linearly to obtain a time series of wind power output at half-hourly intervals. To represent scenarios with larger amounts of wind generation, the capacities at existing wind farm locations were scaled up; while this does not fully reflect the spatial diversity promoted by larger, more distributed wind fleets it is adequate for the purposes of this paper and not expected to substantially alter the results.

Although the analysis presented here focuses on wind, it could conceivably be extended to other variable renewable generation such as solar PV, wave and tidal using similar atmospheric or oceanographic modelling techniques.

2.3 Energy arbitrage model

The time series of electricity prices formed an input for the storage arbitrage revenue model. The revenue was calculated using linear optimisation [30] which determines the quantity of electricity bought and sold during each period, subject to the constraints of the storage capacity, maximum charging/discharging rates as well as efficiencies for conversion (the round-trip ratio of energy delivered to energy consumed) and storage (which measures self-discharge of the device). The model assumes the storage operator has perfect foresight of electricity prices; previous work showed minimal reduction in revenue using practical operating strategies compared to perfect foresight [31]. The storage device was assumed to be small relative to the total capacity in the market and its operation did not affect the price of electricity. Further details on the optimisation can be found in [14].

3. Sensitivity Study

The sensitivity study was conducted by individually adjusting key ‘external’ parameters from initial baseline values to investigate the impact of each factor on arbitrage revenue. These parameters included gas and carbon prices, average capacity margin and installed wind capacity. In a future energy system these would not vary independently of each other and additional variables, such as thermal generation capacity and underlying patterns of demand, would also change; however, these were kept constant to investigate each effect in isolation and gauge its significance.

The baseline case used historic data from 2006, including time series of fuel [32] and carbon [26] prices, generation capacity [33], demand times series [34] and wind speed time series [27]. This ensured a degree of coherence in the underlying data. The installed capacity of each class of generator is: 12 GW nuclear, 26 GW coal, 22.6 GW CCGT, 12 GW OCGT, 1.9 GW onshore wind and 300 MW offshore wind [33]. Installed wind capacity was less than 3% of the total generation capacity and typically, coal generation was dispatched before CCGT in the merit order.

Initially, the storage characteristics were fixed at the baseline values listed in Table 3. These depict a moderate scale device with a power-to-storage ratio of 1:10, reasonable round trip efficiency and no other losses.

Table 3 *Baseline storage characteristics.*

Storage Constraint	**Unit**	**Value**
Maximum storage capacity	MWh	200
Maximum charging/discharging rate	MW	20
Conversion efficiency (round trip)	%	75
Storage efficiency	%/day	100

4. Market Variables

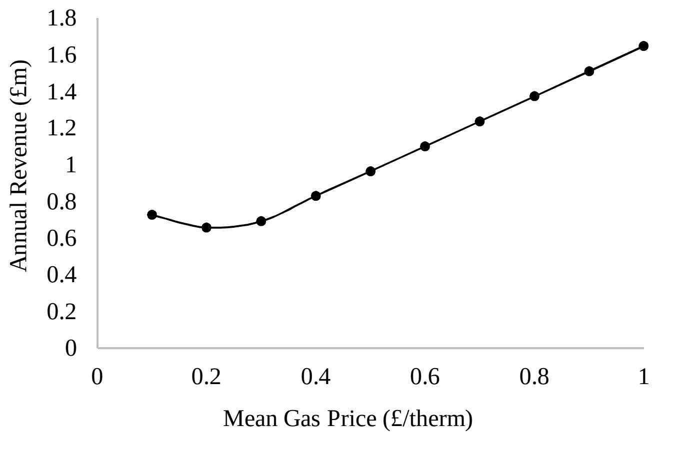
4.1 Gas Price

The 2014 National Grid FES [35] estimates that, in a high price scenario, gas prices would be slightly less than £1/therm by 2035. The arbitrage algorithm was therefore run for simulated electricity prices with average gas prices increasing from 10p/therm (£3.41/MWh) to £1/therm (£34.13/MWh). Gas prices are volatile and have varied over this range of values in the last ten years. For reference, the average gas price in 2015 was approximately 50p/therm (£17.07/MWh) [32]. For each average gas price, the remaining inputs from the baseline year were used and the electricity price simulated at each half hour for 365 days to enable the annual revenue to be determined. The time series of historic gas prices from the 2006 baseline year was scaled in each case to maintain a constant intra-annual volatility of gas prices for each run.

Fig. 3a shows that for gas prices greater than 30p/therm the arbitrage revenue increased approximately linearly with gas price. Gas turbines were the most expensive thermal generators dispatched and their marginal prices set the daily peak electricity prices. Fig. 3b shows the storage device state of charge over a two week period with an average gas price of 40p/therm and £1/therm. This shows that the optimum operating schedule in both cases was almost identical. The device charged and discharged on a daily basis in line with daily demand cycles. Wind power output had little influence on electricity prices compared to variations in demand as the baseline installed capacity was small. Despite the similar storage operational pattern, the higher gas price led to a larger daily price spread enabling more revenue to be made during each cycle.

Interestingly, for the lowest gas prices, revenue increased. This was because the lowest gas prices reduced the marginal generation cost of gas sufficiently that it became cheaper than coal for some periods. During these periods, coal was the marginal generator and CCGT contributed to base load during some off peak hours. Lower gas prices reduced the price of off peak generation which increased the daily price spread, enabling more revenue to be achieved during a storage cycle.

Fig. 4a shows the marginal generation costs across the year with an average gas price of 10p/therm. This shows periods where coal had the highest marginal generation cost and was dispatched as peaking plant. Fig. 4b shows the marginal generation costs with an average gas price of £1/therm, which shows that OCGTs were the most expensive generator for all periods of the year. The variation in marginal costs for each generator type are a result of the time series of fuel prices used (daily gas, monthly coal and quarterly nuclear prices).



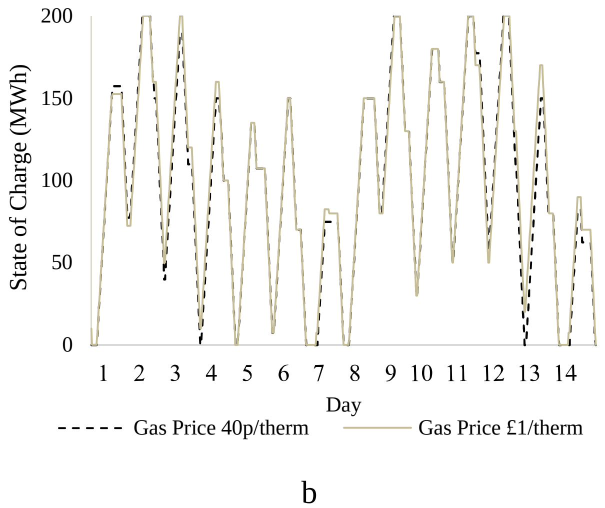
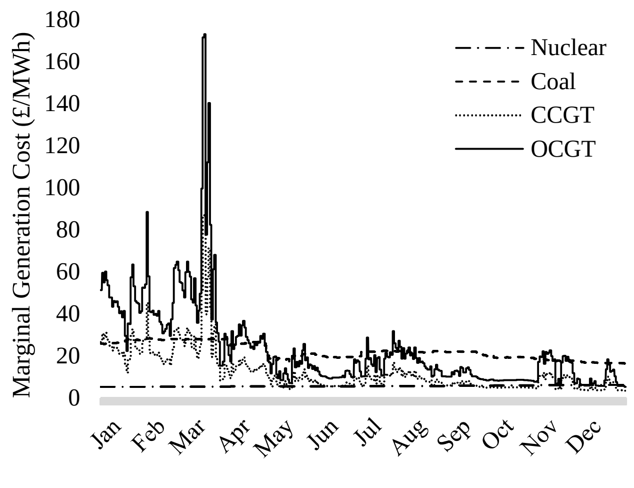


Fig. 3. *Impact of gas prices on (a) annual storage revenue with range of prices and (b) storage state of charge for two winter weeks with gas price of 40p/therm and £1/therm.*



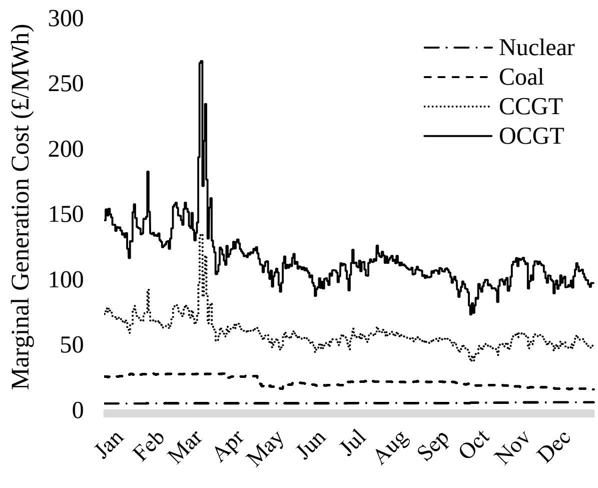


Fig. 4. *Marginal generation costs with average gas prices of (a) 10p/therm and (b) £1/therm.*

4.2 Carbon price

Historically, the carbon price has always been below £20/tonne [26] and the 2014 National Grid FES [35] estimate that by 2035 it could increase to between £30/tonne and £75/tonne. The analysis was repeated for average carbon prices from £10/tonne (£0.01/kg) to £100/tonne (£0.1/kg). The time series of carbon prices within the year was scaled from 2006 to the average value.

Fig. 5a shows that revenue increased with carbon price, albeit at a diminishing rate. Increasing the carbon price increased both gas and coal marginal generation costs, but did not affect nuclear generation costs. For many periods, increasing the carbon price raised the daily peak electricity prices, increasing the price spread and enabling the storage device to gain additional revenue. For other off peak periods the second marginal generator – commonly coal – was required, which set the off peak electricity prices. Increasing the carbon price increased coal generation costs more significantly than gas generation costs, reducing the price spread during periods where coal was required for off peak generation. As the carbon price increased further the price spread – and opportunity for arbitrage – was reduced during these periods, leading to diminishing gains in revenue.

The storage device followed a similar strategy to that shown in Fig. 3b over the range of carbon prices investigated. The storage revenue was significantly less sensitive to carbon price than to gas price. There was an increase in revenue of less than 30% with an order of magnitude increase in carbon price (from £10 to £100/tonne). This compared to an increase in revenue of over 125% for an order of magnitude increase in gas price (from 10p to £1/therm). This demonstrates the relatively modest influence of the current range of expected carbon prices on arbitrage revenue compared to the impact of gas prices.

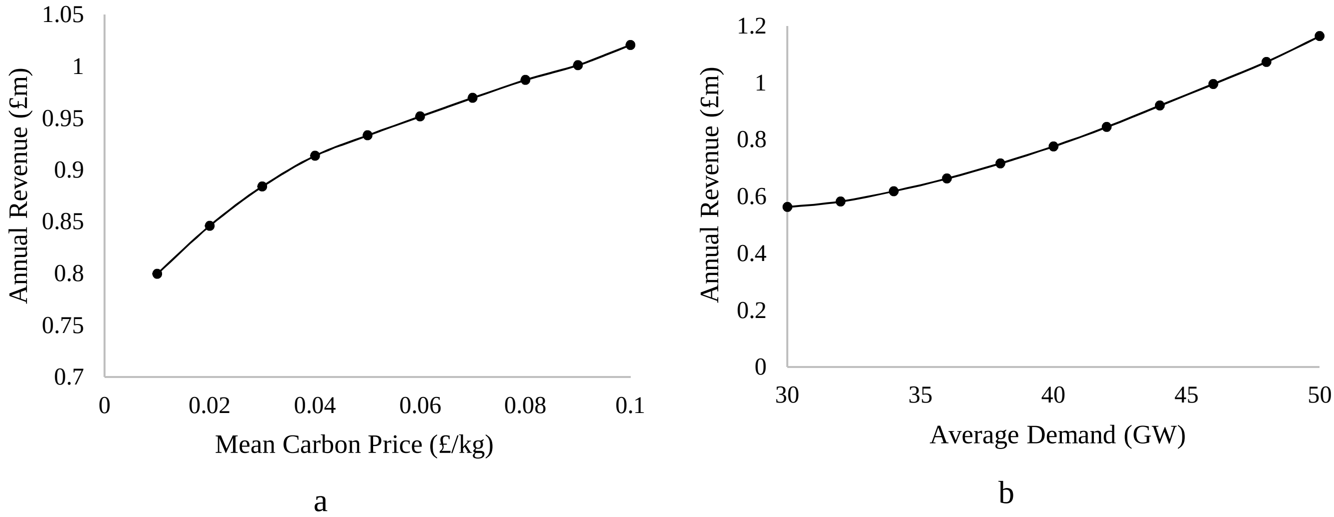


Fig. 5. *Variation in annual storage revenue with (a) carbon price and (b) average annual demand as a proxy for capacity margin*

4.3 Capacity Margin

Retaining the underlying pattern of demand from 2006 and with peak demand kept constant, average demand was varied from 30GW to 50GW to investigate the impact on storage revenue. Generation capacity was fixed at 2006 levels, so increasing demand represented a reduction in the average capacity margin. In a competitive market, this would lead to increased electricity prices incentivising investors to build more generators. This would, in turn, restore a greater average capacity margin and reduce prices restoring market equilibrium. The static market model used does not reflect these changes, but allows variations in demand to be a proxy for the capacity margin.

Fig. 5b indicates annual revenue increasing as capacity margin falls. For low average demand, representing a high average capacity margin, commonly the low merit order generators were able to serve demand throughout the day. This was delivered by the left hand side of the supply curve shown in Fig. 1. In this region prices are low and price elasticity of supply is also low, demonstrated by the shallow curve, resulting in a small price spread. As demand grew, reducing the capacity margin, the higher merit order generators including peaking plant were required. This was delivered through generation represented by the right hand side of the supply curve. Here, prices are higher, but price elasticity of supply is also higher, demonstrated by the steep shape of the curve. As a result, for the same daily variation in demand, the price spread was increasingly larger enabling higher revenue to be achieved.

As the pattern of demand remained unchanged, the optimum operation strategy was similar across the range of average demand investigated, comparable to that shown in Fig. 3b.

4.4 Installed wind capacity

The arbitrage model was run for installed wind capacity increasing from zero to 40GW. The ratio of offshore to onshore capacity was fixed at 3:2. Again, the remaining inputs, including the wind speed distributions, were taken from the 2006 baseline year. Retaining all other generation capacity as per 2006, 40GW of installed wind represents 35% of the total generation capacity in GB. Fig. 6a shows that the revenue reduced as the wind capacity increased. This was due to lower variation in electricity price with increased wind power output. To illustrate this Fig. 6b shows the wind power output for two winter weeks with 40GW of installed wind capacity and Fig. 6c the resulting electricity prices for cases of 40GW and no installed wind. Prices were similar for both scenarios between days 8 and 9 when the wind power output was nearest to zero. With 40GW of installed wind capacity, peak prices were significantly reduced during periods of high wind power output, which led generally to lower price variation. This is a result of the shape of the supply curve (Fig. 1) which was steep during periods of low wind production, but shallow during periods of high wind production. 40GW of wind capacity reduced scarcity of supply, leading to reduced average prices and although there was increased variation in thermal output there was reduced variation in price; these led to decreasing arbitrage revenue. This is shown clearly in the annual price duration curves (Fig. 6d) with zero and 40GW of installed wind capacity. Prices are generally suppressed with 40 GW wind including at extreme low net demand. Higher peak prices have been suggested to be a natural outcome in a system with high penetrations of wind capacity where peaking plant seeks to recover its fixed costs over fewer operational hours [15], although the operation of a capacity market would tend to transfer these costs out of the wholesale energy market. In common with other models that neglect dynamic pricing changes (e.g. [21]), the increases in peak prices are not seen here. However, the consequent impact on revenue estimates is limited as the constraints on operation of a storage device limit their ability to exploit these sporadic and infrequent price spikes.

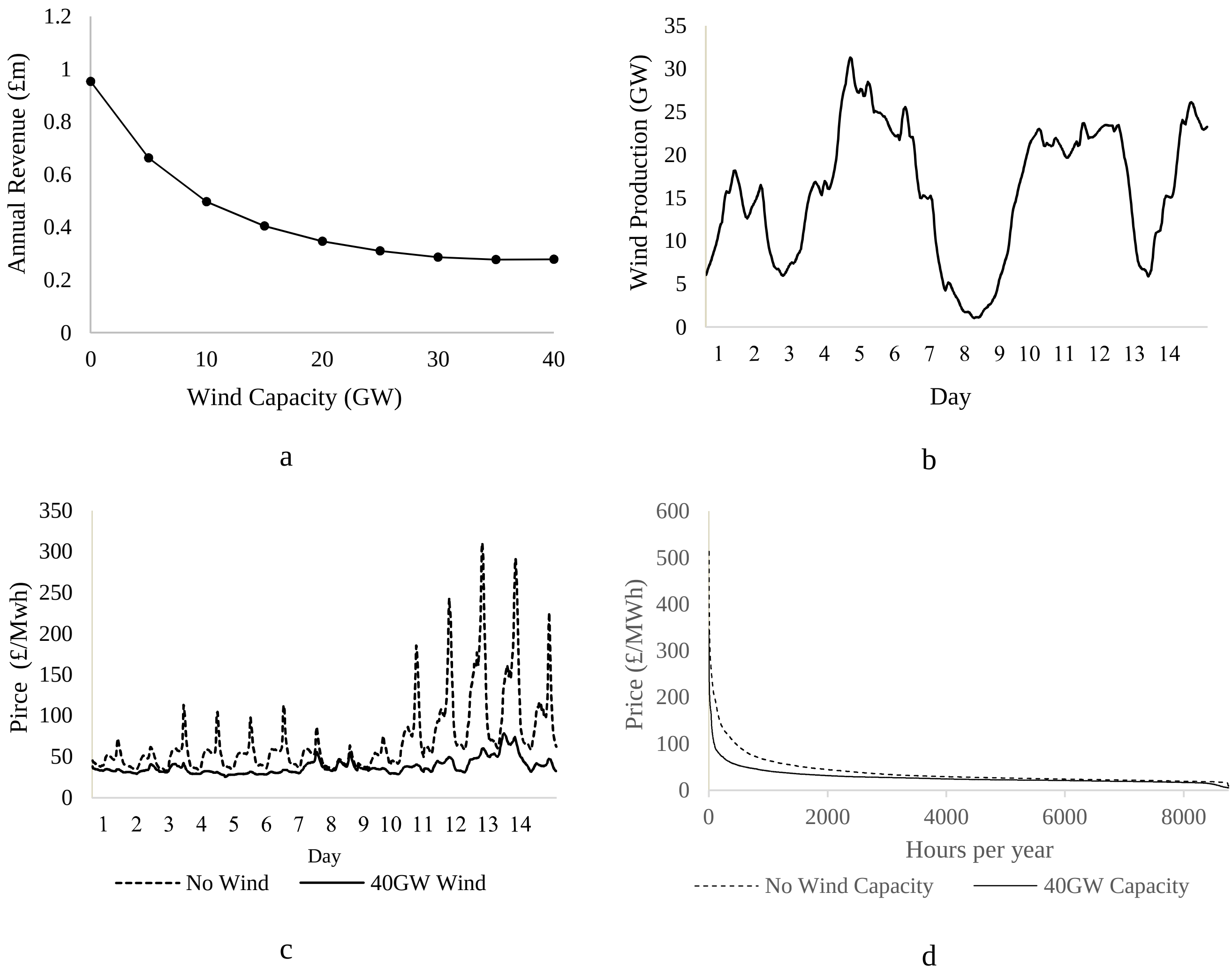


Fig. 6. (a) Impact of wind capacity on annual revenue; for case of 40 GW wind (b) wind production and (c) electricity prices for two winter weeks and (d) annual price duration curve.

Fig. 7 shows the state of charge of the storage device for the same two weeks. With no installed wind capacity the device charged and discharged once a day in line with the variation in electricity price driven by demand patterns. The storage device did not reach its maximum storage capacity or fully discharge on every cycle. With 40GW of installed wind the device charged and discharged less frequently with only four distinct cycles over the two week period. This is similar to the four distinct cycles of wind power output shown in Fig. 6b and is in line with the typical frequency of synoptic weather patterns that dominate UK climate. Additionally with 40GW of installed wind capacity, the storage device was limited for longer periods of time by its 200MWh maximum capacity.

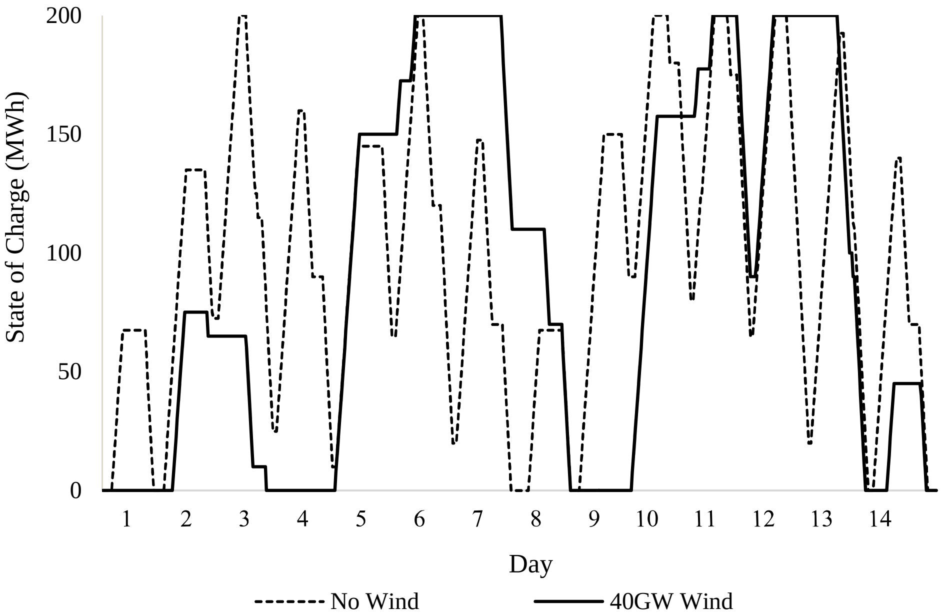


Fig. 7. *Storage state of charge for two winter weeks with no wind and 40GW installed wind capacity.*

4.5 Base Year

For all the variables discussed above, time series of demand and wind speeds were taken from the same 2006 base year. These patterns change from one year to the next and will affect electricity storage revenue. To examine the effect of this the underlying time series of demand and wind speed patterns from different base years were employed with fuel and carbon prices remaining fixed at 2006 levels. Table 4 shows the resulting annual revenue for each of the years. It can be seen that are substantial differences between them with variations of over 100% in revenue from one year to the next. This demonstrates the inherent risk facing electricity storage investors from variations in patterns of demand and wind speeds; factors influenced by circumstances outside even the electricity sector.

Table 4 *Annual revenue from 2006 using alternative base year time series.*

Year	Revenue (£000)
2005	363
2006	821
2007	386
2008	629
2009	401
2010	449

5. Storage System Characteristics

The external factors examined in Section 4 are outside the direct control of electricity storage investors. However, it may be possible to engineer device characteristics to minimise potential negative impacts or enhance the positive impacts of these external factors. Understanding the value of different technology characteristics in the context of changing markets will enable development of storage systems which are robust to uncertain future circumstances.

5.1 Storage capacity and charging rate

The majority of the variables investigated in Section 4 did not affect the optimum operating strategy of the storage device. In these cases, the sensitivity of revenue to storage capacity and charging rate did not change significantly as the variables changed. However, Fig. 7 shows that there was a substantial change in the operating schedule with 40GW of installed wind capacity compared to no installed wind. This suggests that the storage capacity and charging rate may be valued differently in energy systems with different penetrations of wind. This was investigated by comparing the change in annual revenue for devices with increasing storage capacity and charging rate for cases with no installed wind capacity and with 40GW of wind capacity.

Fig. 8a shows the change in revenue with increasing storage capacity and constant charging rate for cases with zero and 40GW of installed wind. The remaining characteristics were fixed at the values listed in Table 3. The results are normalised relative to the revenue from devices with a 600MWh capacity, the maximum investigated for each case: £0.96m and £0.38m for the zero and 40 GW wind cases, respectively. The normalised revenue shows the distinct difference in sensitivity to storage capacity more visibly than the absolute values. Fig. 8b shows the change in revenue with increasing charging rate and constant storage capacity for the same cases, again normalised relative to the revenue from devices with a 200MW charging rate (£2.72m and £0.69m for zero and 40GW of wind capacity, respectively).

Fig. 8a and Fig. 8b show that the rate of increase in revenue falls as storage capacity and charging rate are independently increased. For larger storage capacities the full range was utilised less frequently and increasing the capacity further yielded fewer opportunities to store more electricity and generate additional revenue. Similarly, the highest charging rates were the least restrictive on revenue so increasing them further, with the storage capacity fixed, yielded fewer benefits. With no wind capacity, the arbitrage revenue was much less sensitive to the storage capacity than with 40GW of wind, however, it was more sensitive to the charging rate. With no wind, the storage performed best by charging and discharging on a daily basis limited by the maximum charging rate on each cycle, as seen in Fig. 7. With 40GW of wind capacity, however, the storage performed best by charging, discharging and storing energy over longer periods of time with fewer cycles, leading to the capacity becoming the more restrictive constraint. These results suggest that devices with higher storage capacity to power ratios may perform better in markets with a large penetration of wind power.

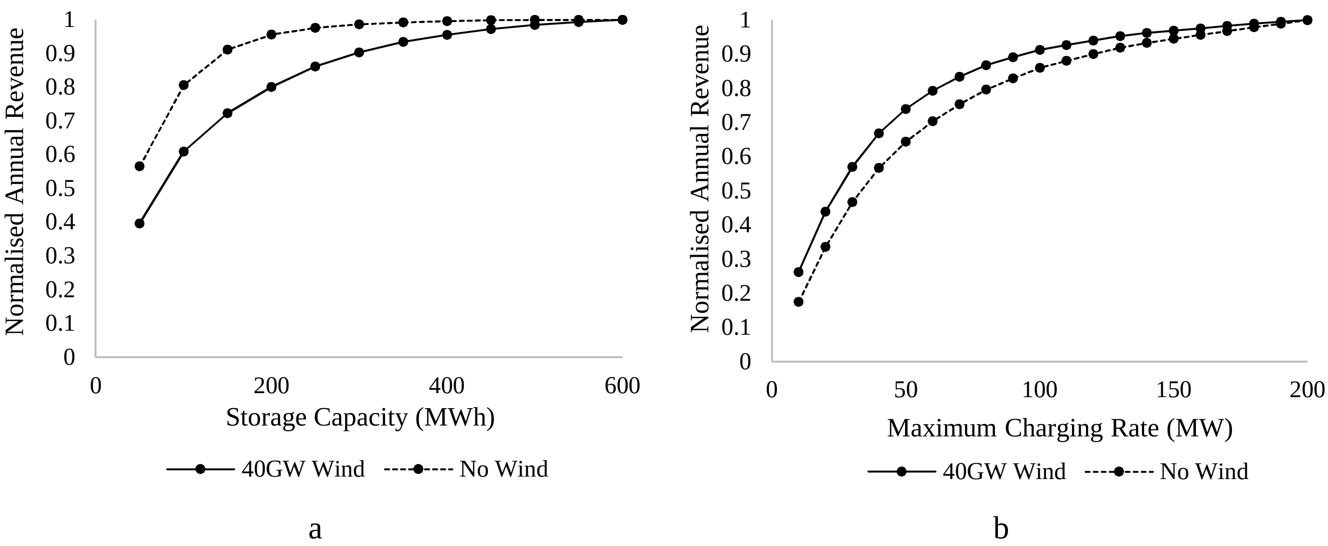


Fig. 8. *Annual revenue for zero and 40GW installed wind capacity cases with other variables fixed at baseline: (a) varying storage capacity with fixed charging rate, normalised relative to 600MWh storage capacity and (b) varying charging rate with fixed storage capacity, normalised relative to 200MWcharging rate.*

5.2 Efficiency

In any energy market, arbitrage revenue will be sensitive to the round-trip efficiency and self-discharge of a device. With higher electricity prices, conversion losses are relatively more costly. Increasing fuel and carbon prices led to higher electricity prices and increased sensitivity to round-trip efficiency and self-discharge. Increased wind capacity, on the other hand, led to frequently reduced electricity prices. However, this led to increased sensitivity to round-trip efficiency and self-discharge, as shown in Fig. 9a and b. The higher levels of wind power not only reduced average electricity prices but also reduced the variation between wholesale price peaks and troughs. As a result, conversion processes needed to be *more* eficient to return the same revenue. Furthermore, with high wind penetrations, electricity prices cycled over longer durations and energy was stored over longer periods making revenue more sensitive to self-discharge.

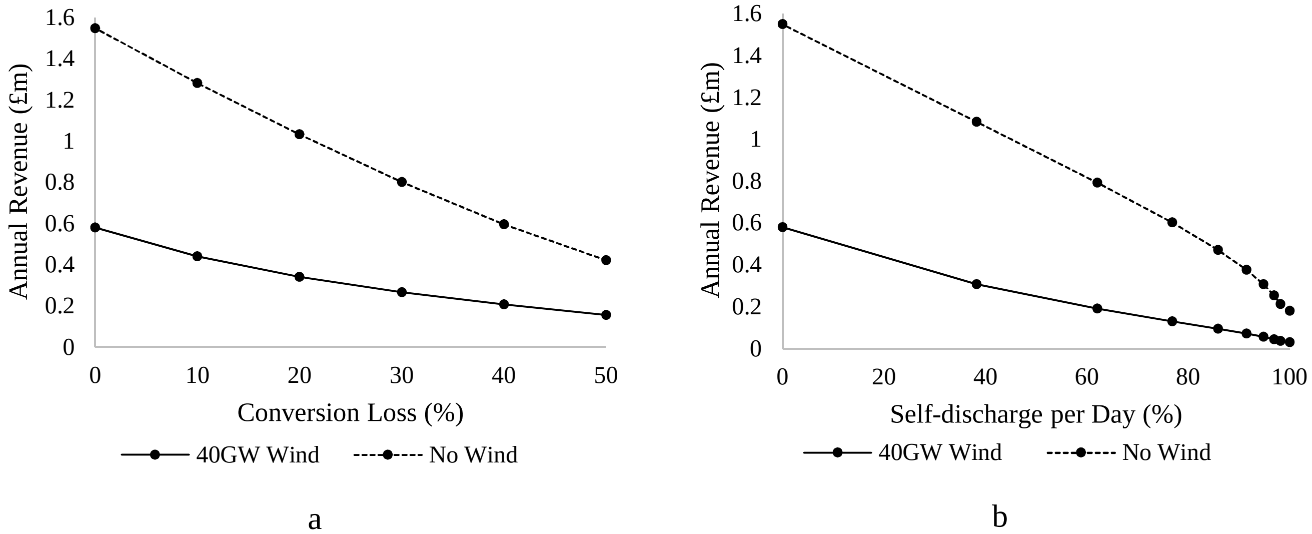


Fig. 9. *Annual revenue for high and low installed wind capacities, varying (a) conversion losses with zero self-discharge and (b) self-discharge with zero conversion losses.*

6. Conclusions

As the electricity system incorporates increased renewables there will be changes in electricity price which will affect the operation of and business case for energy storage. This paper demonstrates the impact of a range of uncertain market variables on price arbitrage opportunities and how different storage characteristics are rewarded. Systematic examination of the sensitivity of revenue to key external factors showed that revenue rose with increasing gas price, carbon price and demand, but fell as wind capacity increased. Further, as well as uncertain mid- to long-term market conditions storage revenue was sensitive to inter-annual variations in wind speeds and demand and the economic, climate and behavioural patterns that drive them. Increased wind capacity is found to substantially impact the revenue available to storage, but also the way in which is it operated. With higher wind penetration, wholesale prices became more strongly influenced by wind power output than by diurnal patterns of demand behaviour. This reduces the number of storage cycles and leads to energy being stored for longer periods. As a result, revenue becomes more sensitive to storage capacity and efficiency, but less sensitive to charging rate. Revenue also becomes more dependent on conversion efficiency as the variation between wholesale price peaks and troughs was reduced. As storage characteristics designed for current market conditions appear not be optimal as wind penetration rises, smaller modular storage devices which could be expanded independently as the electricity system evolves, may offer safer investment options than large, monolithic projects.

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